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Adaptive Thresholding Based Image Segmentation with Uneven Lighting Condition

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***Abstract*—We propose two new schemes for segmentation of images with uneven lighting conditions. These are based on adaptive window selection. The first one is a window merging method based on Lorentz information measure (LIM) but the second one is a window growing method using the notion of entropy. We propose two new window merging criterion where the window merging is carried out based on linear combination of local and global statistics. In window growing method, we define a notion of feature entropy and the window is selected employing jointly entropy and feature entropy. The two window merging schemes perform better than the schemes using only LIM. The proposed window growing technique is compared with schemes using only LIM and the proposed two merging techniques. It is found that window growing technique is best among all in the context of error due to misclassification error.**

Keywords- Entropy; image Segmentation; uneven lighting; window merging

I. Introduction

Thresholding technique has successfully been employed for image segmentation for last three decades [1]-[5]. It has proven to be quite useful to separate object and background in a given scene [6]-[9],[12] or discriminate among objects having distinct gray levels. Thresholding can be categorized as bilevel and multilevel. Bilevel classifies pixels into two groups, one including pixels with gray levels above a threshold and the other with gray levels below the threshold. Multilevel thresholding has multiple thresholds and groups the pixels having gray level within a threshold. The thresholding based methods can be broadly classified as non parametric [1] and parametric [2]. The existing techniques can be viewed as either fixed [1]-[6] and, or adaptive [8]-[13]. Otsu's method [1] is a non parametric one and yields an optimal threshold to minimize the intra class variances and maximize the inter class variances. Kittler's [2] formulation is in stochastic framework where attempts have been made to minimize the error due to overlapping class distributions. In the early stage of research on thresholding, there was predominant focus on global thresholding with different notions. Entropy, cross entropy and minimum entropy were some of the potential attributes [3]-[6] used for quite sometime to determine the optimal threshold for image segmentation. The reported results are quite promising but these techniques have little impact on segmentation of images with uneven lighting conditions. Parker [7] suggested a scheme for segmentation of images under badly illuminated condition. Recent research on thresholding addresses these problems with the concept of adaptive thresholding [8]-[9],[11],[13] . By and large, adaptive techniques use the local as well as global measures of the images [9]-[11],[13].

Adaptive threshold based on window merging was proposed by Huang et al. [10] where the proposed merging criterion is based on Lorentz information measure (LIM). The window merging criterion is based on pyramid data structure manipulation. This yielded accurate segmentation under uneven lighting condition but the result was found to be greatly dependent on the proper choice of initial window size. Recently adaptive block image thresholding is proposed [11] while maintaining image continuity. A multilevel thresholding based algorithm is proposed by Hammouche et al. [13] where wavelet transform is used for different scales and the thresholds are determined by Genetic algorithm. A parallel Genetic algorithm based object background classification is also proposed by Kanungo et al. [12].

Yan et al. [9] uses the local image statistics of mean and variance within a variable neighborhood for two thresholds from global intensity distribution. The method could be successfully tested on images with poor illumination.

In this paper, we propose adaptive thresholding techniques based on window merging and window growing. We propose two new window merging criteria using the notion of Lorentz information measure. In this method, we partition the image into fixed number of windows and test each window to be merged with the neighboring windows to double the size of the original window. The first merging criterion is based on the weighted combination of the local statistics of of gray level over the window and the global statistics of the Lorentz information measure. The testing condition depends on the global statistics of the Lorentz information measure around Otsu's threshold. The merging is adaptive in nature in the sense that once the window is merged, the merged window is considered as a new window and the process is repeated. The second merging criterion is based on the weighted combination of local statistics of the gray level distribution and the local statistics of the Lorentz information measure. The testing criterion is based on the global statistics of the Lorentz information measure. Both the schemes are iterative in nature

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and could successfully be tested for uneven lighting condition. The weights in these schemes are selected on the basis of trial and error. It is found that the final segmentation depends on the proper selection of initial window size. In order to circumvent this problem, we propose another scheme where the window grows, starting from a small size of the window, as opposed to window merging. We compute the edge map of the window and entropy of this edge map is considered as the feature entropy. The entropy of the window is also computed. These two entropies serve as local information measure. The window size is fixed depending on the simultaneous testing of entropy and the feature entropy. The testing condition is an entropy that is a fraction of the total entropy of the image. The window growing scheme was successfully tested on different images having uneven lighting conditions and the performance is found to be better than that of Lorentz information measure and the two proposed window merging based schemes.

II. Window merging based Adaptive thresholding

A. Lorentz information measure

The window merging is based on the use of Lorentz information measure. In the following, we explain the Lorentz information measure [10].

Let us consider an image $X(m,n)$ having G gray levels. The amount of information contained in this image is called as picture information measure (PIM) and that indicates the least gray level variation when converting the image $X(m,n)$ to a constant gray level image and PIM can be expressed by

$$PIM(x) \quad = \quad \sum_{i=0}^{G-1} h(i) - \max_i h(i) \qquad (1)$$

where h is the gray level histogram of $X(m,n)$, $h(i)$ represents the gray level histogram of $X(m,n)$. $PIM(x) = 0$, if $X(m,n)$ consists of a constant gray value and $PIM(f) = max$, when the gray level histogram $h(i)$ is uniformly distributed. Thus, when $X(m,n)$ has the least information, $PIM(x)$ has its minimum value; and when $X(m,n)$ has the most information, $PIM(x)$ has its maximum value. Assuming that total number of pixels of $X(m,n)$ is $N(x)$, the normalized PIM (NPIM) can be determined by

$$NPIM(x) \quad = \quad PIM(x)/N(x) \qquad (2)$$

Defining the probability p_i as $h(i)/N(x)$, the normalized $PIM(x)$ can also be expressed as

$$NPIM(x) \quad = \quad 1 - \max_i \; p_i, \qquad (3)$$

Thus, PIM_k can be defined as

$$PIM_k(x) \quad = \quad \sum_{i=0}^{G-1} h(i) - \sum_{i \in \theta(k)} h(i), 0 \le k \le G \qquad (4)$$

where k is the number of k highest values of $h(i)$, and $\theta(k) = \{k \text{ highest values of } h(i)\}$. It indicates the minimum variation number that converts an image to the image with k gray levels. Correspondingly, normalized PIM_k is denoted as $NPIM_k$ and is obtained by

$$NPIM_k(x) \quad = \quad 1 - \sum_{i \in p(k)} P_i, \quad 0 \le k \le G \qquad (5)$$

where $p(k) = \{\text{the } k \text{ maximum numbers of } p_i\}$. Let $S_k = NPIM_{G-k}(f)$, $0 \le k \le G$, then

$$S_0 = 0, \quad S_G = 1, \quad S_k = \sum_{i=0}^{k-1} p_i \qquad (6)$$

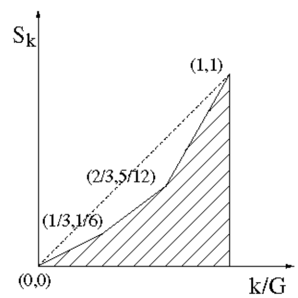


Fig. 1. Example of Lorentz information curve (G=3)

By connecting the points $(k/G, S_k)$, $k = 0, 1, ..., G$, a broken line called Lorentz information curve can be obtained. For the sake of illustration, Fig. 1 shows a Lorentz information curve with $G = 3$, in which the histogram is h : $\{N/6, N/4, 7N/12\}$, with N being the total number of pixels in an image.

The area defined below the Lorentz information curve (area under the oblique lines in Fig. 1) is the Lorentz information measure LIM$(p_0, p_1, ..., p_{G-1})$. When the gray level histogram of image is uniformly distributed, its Lorentz information curve becomes a line from (0,0) to (1,1) (dashed line in Fig. 1). Otherwise, it will be the convex broken line below the dashed line (solid line in Fig. 1). So when LIM$(p_o, p_1, ..., p_{G-1})$ increases, the image contains more information; as LIM$(p_o, p_1, ..., p_{G-1})$ decreases, the image has less information, and vice versa.

This Lorentz information has been used as the window merging criterion by Huang et al. [10] and segmentation is carried out using Otsu's criterion.

B. Window merging based on weighted local and global statistics

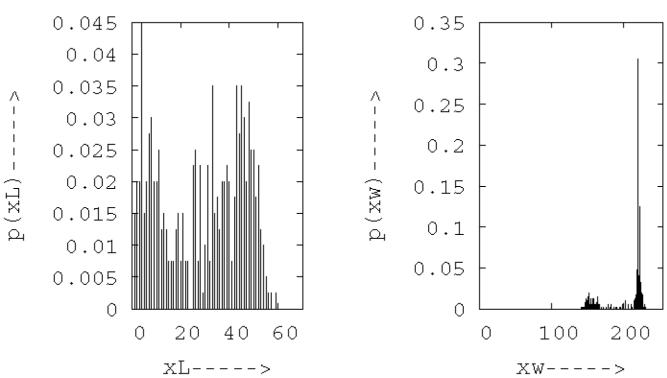
It has been found in section II (A) that determination of window size based only on Lorentz information measure did not yield proper segmentation and hence there were quite a bit of misclassified pixels. In this section, we introduce a new measure of window merging taking into account the local and as well as the global statistics. The given image is partitioned into a set of windows of chosen size. For the sake of illustration, for a (128 × 128) image, 16 windows of size((32 × 32) can be obtained by partitioning. After partitioning W_k denotes the kth window and L_k denotes the

Lorentz information of the kth window. In each window, Lorentz information measure is computed and LIM of each window is considered as a feature of the window. Then the histogram of these features for all the windows is determined. This indicates the distribution of Lorentz information of the whole image. Thereafter histogram of each window is also computed and this provides the local information.

The proposed window merging criterion is based on the weighted combination of local and global statistics and expressed as the following.

$$a_1\ \sigma_{wh} + a_2\ \sigma_{fh(LIM)} > \sqrt{\sum_{i=1}^{n_w} (x_{i_{fh}} - T_{fotsu})^2} \qquad (7)$$

where σ_{wh} denotes the standard deviation of the histogram distribution of the window considered for merging, $\sigma_{fh(LIM)}$ denotes the standard deviation of the feature histogram, a_1 and a_2 are the associated weights. Right Hand Side (RHS) of (7) indicates the standard deviation of the featured histogram with a mean determined by Otsu's method. Fig. 2(a) shows the histogram of the feature of the entire image, that indicates the spread of Lorentz information of the image. Fig. 2(b) shows the histogram of the gray value of the window. Thus, in (7) the spread of gray value and the spread of the feature is given due weightage. $x_{i_{fh}}$ denotes the LIM of the ith window in the featured histogram and T_{fotsu} denotes the threshold by Otsu's method for the featured histogram. In other words, RHS of (7) denotes the spread of the feature (LIM) around Otsu's threshold. If (7) is satisfied, the window is considered for segmentation else the window is merged to double its size. The new merged window is considered as a new window for the next iteration. This process is iterated till no more window merging takes place. Thereafter, each window is segmented based on Otsu's method.



(a) (b)

Fig. 2. (a) Histogram of feature (LIM) (b) Histogram of a window

C. Local statistics based window merging

We also propose another window merging criterion. In this case, the notion of merging is based on the comparison of local information with the global information. Analogous to the previous criterion, the image is partitioned and the histogram of the feature (LIM) is found out. The criterion is expressed as follows

$$a_1\ \sigma_{wh} + a_2\ LIM_w > T_{fotsu} \qquad (8)$$

where σ_{wh} denotes the standard deviation of histogram of a given window , LIM_w denotes the Lorentz information of the window. T_{fotsu} denotes the threshold of the feature histogram, obtained by Otsu's method. LHS of (8) may be viewed as a locally biased LIM, that is compared with the threshold (Otsu's method) determined from the feature histogram of the total image. This Otsu's threshold correspond to a LIM and hence the biased local LIM is compared with the threshold corresponding the information measure. The salient steps of the algorithm are enumerated as follows.

Algorithm

1) Choose a size of the window and partition the image into sub images.
2) In each window, compute the histogram and consider LIM of the window as a feature.
3) Compute the histogram of the feature (LIM) for the entire image.
4) Choose the weights a_1 and a_2 of (7) and (8) and test for merging the windows. If the window needs merging, the window is merged with the neighboring windows so that the size is doubled.
5) Repeat step 2-4 till none of the windows needs merging.
6) Each window is segmented based on Otsu's method. Final segmentation is the union of segmentation of all the windows of the image.

III. Entropy based window growing

The proposed methods of section II are based on the Lorentz information measure and is predominantly dependent on the proper choice of initial window size. In order to ameliorate this situation, we propose a method of window growing instead of window merging.

The basic notion of window growing is to fix the window size primarily focussing on the information measure of the image at different scale. In other words, fixing of size of the window not only depends on the entropy of the chosen window but also the feature entropy of the window. The edges of the window are considered as the features and the feature entropy is computed. Since, the edge map represents the image information at a different scale, the entropy at this scale also plays a pivotal role for image segmentation. Thus, the basic notion is to capture the information at a different scale. It is known that entropy can be expressed as

$$H_w = \sum_{i=1}^{G} p_i\ \ln\left(\frac{1}{p_i}\right) \qquad (9)$$

where p_i is the probability distribution of the ith gray value, H_w denotes entropy of the window, G denotes the total number of gray values. Over a given window, the edge map is computed and the entropy of the edge map is

$$H_{wf} = \sum_{i=1}^{G} p_{f_i} \ \ln\left(\frac{1}{p_{f_i}}\right) \tag{10}$$

where H_{wf} denotes the entropy of the edge map of the window. The following are the two proposed window growing criteria.

Case I: (WG-I)

The window is fixed if the following is satisfied

$$H_w > Th \tag{11}$$

where Th is selected based on the entropy of the total image.

Case II: (WG-II)

The following criterion is considered for window fixing after window size grows.

$$H_w > Th$$

$$subject\ to\ the\ constraint,\ H_{wf} > Th_f \tag{12}$$

The thresholds Th and Th_f for the above inequalities are chosen based on the total entropy of the image and that of edge map respectively. Empirically, it is found that the thresholds are closer to the entropy of the whole image and whole edge map. The salient steps of the algorithm are given below.

Algorithm

1) Choose a window of size $(w \times w)$.
2) Determine the entropy from the gray value distribution of the considered window.
3) Compute the edge map and determine the feature entropy of the edge map of the window.
4) Choose two thresholds Th and Th_f and test the conditions of the (11) and (12).
5) If the window is fixed, then start from the next window. If not fixed, then increase the window size by 10% to 25%.
6) Repeat steps 2-5 till the whole image is exhausted.
7) After the windows are fixed, Otsu method is applied to obtain threshold and hence segmentation.

IV. Simulation

We have tested our window merging and window growing schemes for a variety of images. For the sake of illustration, we present results for two images to validate window merging and two other images for window growing schemes.

A. Window merging

Fig. 3 and Fig. 4 show the two images considered to test window merging based schemes. One of these images is a synthetic image and the other is a real image with varying lighting conditions. It is seen from the Fig. 3(a) that there is uneven lighting condition for the hexagon image. The left part of the image is darker than the right part. The corresponding histogram is shown in Fig. 3(b) that apparently shows three modes. At the first hand, it appears two thresholds would segment but it will result in a three class image. For object background classification, this should be classified into two classes and hence Otsu's method with bilevel threshold (60) yields a result as shown in Fig. 3(d). The ground truth image is constructed manually and is shown in Fig. 3(c). The misclassification error is 9.89%. Fig. 3(e) shows result obtained by Huang's method of adaptive thresholding.

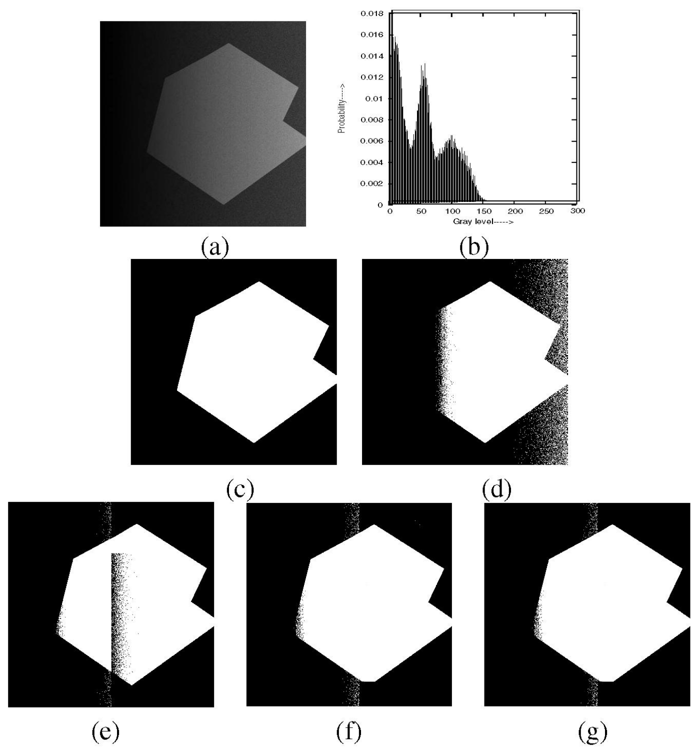


Fig. 3. Segmentation of nonuniform Hexagon image of size (400×400) (a) Original image (b) Histogram of the image (c) Ground truth, Thresholded image using (d) Otsu's method (e) Huang's method (f) Window merging I (WM-I) method (g) Window merging II (WM-II) method

For Huang's method, the image is partitioned into a initial window size of (50×25) and it is seen that although edges could be obtained, part of the hexagon is misclassified as background. As seen from Table I the misclassification error is 2.665%. Fig. 3(f) and Fig. 3(g) show the result obtained by the two proposed methods of window merging. For the first proposed method (WM-I), the initial window size is (50×25) and the two weighting parameters a_1 and a_2 are selected to be 0.24 and 0.76 respectively. It is seen from Fig. 3(f) that there are few pixels misclassified and hence the misclassification error is 1.775%. In the second proposed method (WM-II), the initial window size is (50×25) and the parameters are $a_1 = 0.52$ and $a_2 = 0.48$. The result is visually better than that of first method as the misclassification error also decreased to 1.531%. The weighting parameters are selected on an trial and error basis. Thus, the proposed methods yielded better results than those of Otsu's and Huang's adaptive method.

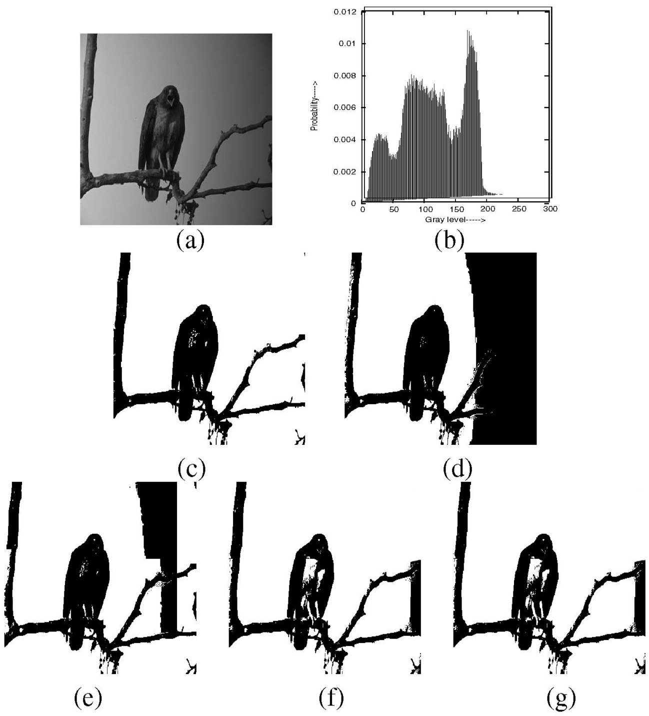


Fig. 4. Segmentation of nonuniform Crow image of size (300×400) (a) Original image (b) Histogram of the image (c) Ground truth, Thresholded image using (d) Otsu's method (e) Huang's method (f) Window merging I (WM-I) method (g) Window merging II (WM-II) method

The second image considered is a real image as shown in Fig. 4(a). The corresponding histogram is shown in Fig. 4(b). The histogram also exhibits modes as if the image has three classes. Therefore, segmentation by Otsu's method as shown in Fig. 4(d) yielded result with large misclassification error. Almost all the poorly lighted part has not been segmented. The ground truth image is shown in Fig. 4(c). Fig. 4(e) shows the result obtained by Huangs method with initial window size of (60×25). In this case also poorly lighted part could not be segmented. The misclassification error is as high as 11.65%. Fig. 4(f) and Fig. 4(g) show results obtained by two proposed methods. In first method WM-I, the window size remained same as that for Huang's method, the weighting parameters are $a_1 = 0.42$ and $a_2 = 0.58$. Some portion of the right hand could not be segmented. Similar situation also happened in case of the second method WM-II as shown in Fig. 4(g). The initial window size is (60×25) and the weighting parameters are $a_1 = 0.61$ and $a_2 = 0.39$. From Table I, it is found that the misclassification error is close to the first method but much less than Huang's and Otsu's method. Thus, the proposed adaptive scheme could segment under poor lighting conditions.

B. Window growing

We have considered two real images with nonuniform lighting. Fig. 5(a) shows a bird image with uneven lighting and the corresponding histogram is shown in Fig. 5(b). Ground truth image is shown in Fig. 5(c). Fig. 5(d) shows the result obtained by Huang's method of window merging. The initial

TABLE I
PERCENTAGE OF MISCLASSIFICATION

Images	Otsu	Huang	WM-I	WM-II
Hexagon	9.89	2.66	1.77	1.53
Crow	31.72	11.46	3.25	3.27

window size is (64×50). It is seen from Fig. 5(d) that there is some misclassification and the misclassification as given in Table II is 14.23%. It is also observed that the darker portion couldnot be segmented. We have applied the proposed window merging methods and the results obtained are shown in Fig. 5(e) and Fig. 5(f). As observed from these figures, some initial portions have been misclassified while the uneven lighting portion have been segmented. The initial window size is (50×25) in WM-II method. Fig. 5(g) and Fig. 5(h) show

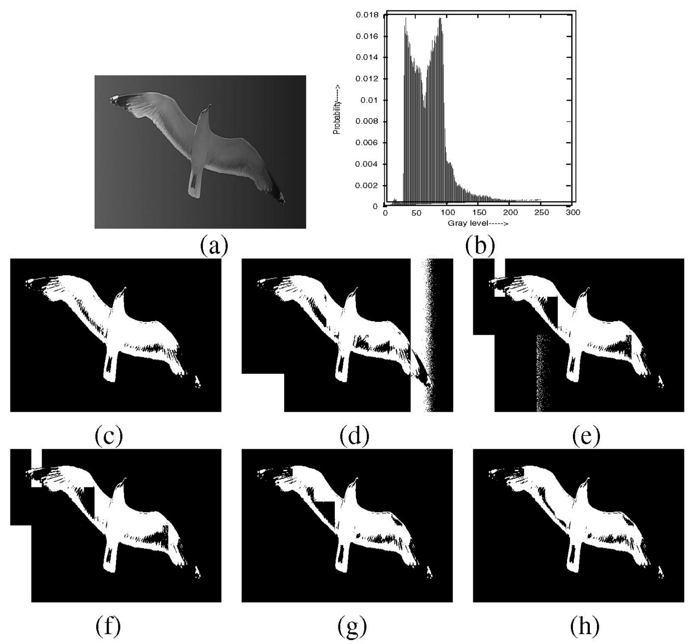


Fig. 5. Segmentation of nonuniform Bird image of size (256×500) (a) Original image (b) Histogram of the image (c) Ground truth, Thresholded image using (d) Huang's method (e) Window merging I (WM-I)method (f) Window merging II (WM-II) method (g) Window growing I (WG-I) method (h) Window growing II (WG-II) method

the results obtained by the window growing methods. Both the methods have yielded good segmentation results as indicated from the Table II. The misclassification error is 1.85% and 1.44%. The initial window size is (64×50) in both the methods and the window size is incremented by (8×10) in each iteration till the window is fixed.

The second image considered is shown in Fig. 6(a) and the corresponding histogram and ground truth are shown in Fig. 6(b) and Fig. 6(c) respectively. Huang's method yielded result with the poor lighting portion assigned to different classes and hence poor segmentation. The WM-I window merging method when applied, yields results with some misclassification pixels and the result is better in WM-II method. The initial window

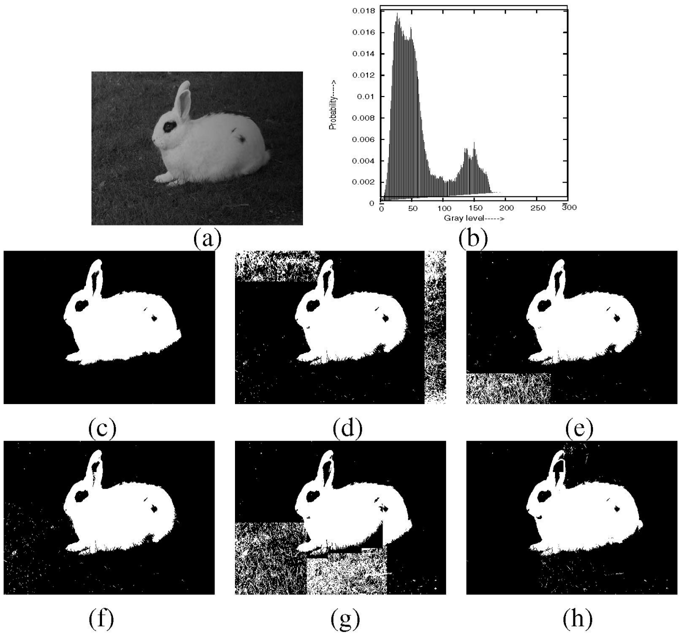


Fig. 6. Segmentation of nonuniform Rabbit image of size (300×400) (a) Original image (b) Histogram of the image (c) Ground truth, Thresholded image using (d) Huang's method (e) Window merging I (WM-I) method (f) Window merging II (WM-II) method (g) Window growing I (WG-I) method (h) Window growing II (WG-II) method

size in both the cases is (60×100) and the weighting parameters for WM-I is $a_1 = 0.3$, $a_2 = 0.7$ and for WM-II $a_1 = 0.8$, $a_2 = 0.2$. The results obtained by window growing methods are shown in Fig. 6(g) and Fig. 6(h). Fig. 6(g) shows that there are many misclassified pixels while WG-II method yielded proper segmentation. This is also reflected in the misclassification error as presented in Table II. The initial window size in both the window growing method is (30×50) and the windows are incremented by a size (10×10). Thus, the feature entropy based window growing technique is found to be better than window merging method.

TABLE II
PERCENTAGE OF MISCLASSIFICATION

Images	Huang	WM-I	WM-II	WG-I	WG-II
Bird	14.23	8.21	7.82	1.85	1.44
Rabbit	8.69	4.66	1.84	2.94	1.09

V. CONCLUSION

In this article, we propose adaptive thresholding techniques for unevenly lighted images employing the notion of window merging and window growing. We propose two new window merging criteria exploring the local and global statistics. The proposed criterion is a linear combination of local as well as global statistics. We have chosen the weighting parameters on a trial and error basis. The results obtained are better than that of using Huang [10] method that uses only Lorentz information. The results of the proposed algorithm are found to be dependent of proper choice of initial window size. We have proposed entropy based window growing techniques. The results obtained by window growing is found to better than the window merging based method. Current work focuses on estimating the weighted parameters and reformulating for other feature entropies.

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